Amendments to the Specification:

Please replace paragraph **[0077]** on page 23 with the following amended paragraph:

Weights on the parameters in the semantic and categorical match component relevancy computation, [[□]] $\underline{\theta}$ and [[□]] $\underline{\alpha}$: [[□]] $\underline{\theta}$ denotes a rate a user wants to consider the irrelevancy measure in his semantic rating and [[□]] $\underline{\alpha}$ denotes how much a user prefers the co-occurrence level to the order consistency level in the categorical match rating.

Please replace paragraph **[0083]** on page 25 with the following amended paragraph:

Furthermore, N^r, N^s, and N^t denote the number of syntactic rules, the number of search engines, and the number of the term combinations, respectively. The symbols, RLPT_i and ILNT_i stand for "relevancy level of positive terms from the *i*-th path in the WSTT" and "irrelevancy level of negative terms from the *i*-th path in the WSTT", respectively. *Rule i* indicates the relevancy level measured by the *i*-th syntactic rule. $\mathrm{CL}_{i,j}$ and $\mathrm{OC}_{i,j}$ also mean the co-occurrence level and the order consistency level between the path *i* and the category information provided by the search engine *j*, respectively. Finally, $\mathrm{RK}^{N}_{i,j}$ stands for a normalized rank information for the term combination *i* from the search engine *j*. The symbols [[□]] $\underline{\Sigma}$, [[□]] $\underline{\Sigma}_1$, [[□]] $\underline{\Sigma}_2$, [[□]] $\underline{\Sigma}_3$, [[□]] $\underline{\Sigma}_4$, and f^* are related to the computational issues. Some of the sub-networks are omitted because of space limitations. The light-shaded nodes denoted with one of [[□]] $\underline{\Sigma}_1$, [[□]] $\underline{\Sigma}_2$, [[□]] $\underline{\Sigma}_3$, and [[□]] $\underline{\Sigma}_4$, have the same sub-network as the node denoting the same symbol; the present invention may only depict the sub-network fully for one of such nodes that have the same symbol.

Please replace paragraph **[0091]** on page 27 with the following amended paragraph:

Before deriving a learning mechanism for the user profile representation, one may note that the model shown in Figure 7 also addresses how the overall computation of the relevancy is performed. In each node, if it is not the leaf node, the relevancy values of the child nodes are aggregated and the symbols appeared in the node represents the aggregation method applied to it. If it is a leaf node, the relevancy value of the node is the input to the model. Each sigma symbol, [[□]] $\underline{\Sigma}$, indicates that the relevancy in the node is computed by the following formula (3) regardless of whether it has a subscript or not in the figure.

Please replace paragraph **[0093]** on page 28 with the following amended paragraph:

In addition, the symbol f^{*} means the relevancy in the node may be computed by the following formula according to the theta propagation rule.

$$O_{pg,j} = (RLPT_i) \bullet (1-\theta)^{ILNT_i} \qquad (4)$$

Where [[□]] $\underline{\theta}$ is a given [0, 1] scale degradation rate and $RLPT_i$ and $ILNT_i$ are the relevancy level of the connected incoming nodes to the node j.

Please replace paragraph **[0095]** on page 28 with the following amended paragraph:

The first problem is that the user profile representation model depicted in Figure 7 differs from the typical feed-forward neural network model in that some of the weights are overlapped and those overlapped weights are required to always have the same value. As shown in Figure 7, the parameters [[□]] $\underline{\theta}$, [[□]] $\underline{\alpha}$, and sw_i are overlapped in multiple places and this means that when each of the weights in the model are adjusted to understand the user's feedback, the

weights that share the same parameter must be controlled to have the same value. A similar restriction also happens in the case of WSTT. The same WSTT depicted in Figure 6 is also used three times in different places of the user profile representation model as shown in Figure 7. Therefore, the weights from different positions but sharing the same parameter, tw^N_i must always have the same value because tw^N_i may not have multiple values at any given time.

Please replace paragraph **[0096]** on page 29 with the following amended paragraph:

To define this problem more precisely, some definitions are necessary. For a given parameter p, if there are multiple weights that share this parameter as their value, this set of weights is called "parameter sharing weight set" of the parameter p and denoted with $PSWS(p)$. In addition, a weight w_{ji} shares by $PS(w_{ji})$. For example, there are three such weights in $PSWS$([[□]] $\underline{\theta}$) as shown in the right-upper side of Figure 7. For all such w_{ji} [[□]] $\underline{\in}$ $PSWS(p)$ for a parameter p, those weights should be always equal to each other. Since the typical neural network learning algorithms may not address this kind of restriction, a way must be devised a way to resolve such a problem.

Please replace paragraph **[0097]** on page 29 with the following amended paragraph:

The second problem is that several sets of weights in the user profile representation model must obey the rule that the sum of the weights in the set should be 1 for the purpose of normalization. At first, the weight sets, $\{w_{ji} \mid PS(w_{ji}) = cw^N_k$ and $k = 1, 2, \ldots, 5\}$, $\{w_{ji} \mid PS(w_{ji}) = sw_k$ and $k = 1, 2, \ldots, N^s\}$ for each node j denoted by [[□]] $\underline{\Sigma}_4$, and $\{w_{ji} \mid PS(w_{ji}) =$ [[□]] $\underline{\alpha}$ or 1 - [[□]] $\underline{\alpha}\}$ for each node j denoted by [[□]] $\underline{\Sigma}_3$ follow this rule. In addition, each set of weights on the nodes that have the same parent in the WSTT also follows this rule. All these weight sets

that follow the rule are called "normalization weight sets" and the set of such sets is denoted by *NWS*. To address this problem, a normalization method is needed while learning is performed.

Please replace paragraph **[0100]** on page 30 with the following amended paragraph:

At first, to apply the generalized delta computing rule, a delta in a node *j* for a feedback Web page *pg*, [[□]] $\underline{\delta_{pg,j}}$ is defined as follows:

$$\delta_{pg,j} = \left\{ \begin{array}{ll} rv^U(pg) - rv(pg) & \text{if } j \text{ is an output node} \\ \sum_k \delta_{pg,k} w_{kj} & \text{otherwise} \end{array} \right\} \qquad (5)$$

where *k* is a node in the upper layer to the layer to which the node *j* belongs.

Please replace paragraph **[0101]** on page 30 with the following amended paragraph:

Using this delta, a weight-updating rule may be derived as follows:

$$w_{ji}^{updated} = w_{ji}^{old} + \eta \bullet \delta_{pg,j} \bullet o_{pg,i} \qquad (6)$$

where [[□]] $\underline{\eta}$ is a learning rate for the weight.

Please replace paragraph **[0103]** on page 31 with the following amended paragraph:

Then, use (6) for updating the parameter [[□]] $\underline{\theta}$ in the f^* function but since the value of the incoming node of this [[□]] $\underline{\theta}$ connection is always fixed to 1, its theta updating rule may be simplified as follows:

$$\theta_j^{updated} = \theta_j^{old} + \eta \bullet \delta_{pg,j}^{\theta} \qquad (8)$$

where the [[□]] $\underline{\theta_j}$ is a corresponding [[□]] $\underline{\theta}$ in a $\underline{f^*}$ type node *j*.